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Community vulnerability to coastal hazards: Developing a typology for disaster risk reduction

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ABSTRACT

Coastal communities around the world face challenges in planning for coastal flooding and sea-level rise related to climate change. This paper develops an approach for identifying typologies of communities on the basis of their hazard vulnerability characteristics. The approach first characterizes communities with a suite of vulnerability indicators, selected to meet criteria of breadth, relevance, and data requirements. Cluster analysis is then applied to the indicator profiles to identify groups of similar communities. The statistical centrotype of each group represents the corresponding community type. A new community from outside the original set can then be matched to the typology using a Hazard Vulnerability Similarity Index (HVSI). The approach is demonstrated with a case study of 50 communities on Canada's Pacific coast. Results yielded 10 community types, of which four were predominant. The types range from highly urbanized, wealthier, diverse central cities to remote, resource-dependent towns with semi-developed, flat coastlines. Three selected communities from a distant region, in Atlantic Canada, were then successfully matched to the most similar of these 10 types. Identifying groups of communities that share vulnerability profiles can facilitate sharing knowledge, lessons, and resources that are most relevant to local efforts to reduce natural hazard risk. This support may be especially valuable for connecting communities that are unfamiliar with one another, yet similarly vulnerable.

1. Introduction

Around the world, coastal communities face hazards such as coastal flooding and sea-level rise related to climate change (Revi et al., 2014). Total potential losses from flood hazards are increasing rapidly in major coastal cities (Hallegatte, Green, Nicholls, & Corfee-Morlot, 2013). While many cities have initiated adaptation to coastal hazards through planning and engineering efforts, others lack the knowledge and resources to implement appropriate risk reduction measures (Araos et al., 2016; Bierbaum et al., 2013). The multidimensional nature of climate impacts and growing demand for knowledge to support adaptation necessitate exchange through social learning networks that span multiple sectors and communities (Bidwell, Dietz, & Scavia, 2013). The proliferation of urban climate adaptation and resilience networks (e.g., 100 Resilient Cities, C40 Cities Climate Leadership Group, ICLEI–Local Governments for Sustainability) attests to the increasing demand among communities to share knowledge and resources on risk reduction strategies, experiences, and lessons.

Knowledge sharing may be especially valuable between communities with similar vulnerability characteristics (Chang, Yip, van Zijll de Jong, Chaster, & Lowcock, 2015; Wood, Jones, Spielman, & Schmidtlein, 2015). Vulnerability, which has been conceptualized in multiple, evolving, and sometimes incongruent ways in the literature (Wisner, 2016), is here defined as attributes of communities that affect the potential for harm when hazard events occur. Vulnerability arises as "a function of the exposure (who or what is at risk) and sensitivity of the system (the degree to which people and places can be harmed)" (Cutter et al., 2008, p. 599). Factors such as coastal geomorphology, urban development patterns, wealth, and socio-economic structures affect how a given coastal hazard event would lead to human losses, property damage, and economic disruption (IPCC 2012). To be effective, therefore, risk reduction and resilience strategies must consider the local hazard and vulnerability context, as solutions appropriate for some types of communities may be unsuitable for others (Wood et al., 2015).

This paper contributes to the emerging literature on patterns of vulnerability across places. Numerous studies have advanced understanding of vulnerability by identifying localities that are highly vulnerable, thereby focusing policy attention and resource allocation. Recent scholarship has advocated a complementary goal: recognizing

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how places may be similarly vulnerable, regardless of whether or not they are highly vulnerable, in order to facilitate knowledge exchange for risk reduction. To address this need, this paper develops a method for identifying groups of similarly vulnerable places and applies it to empirically derive a typology of communities at risk from coastal flooding.

2. Indicator-based vulnerability analysis

Place-based indicators have been applied extensively in research and practice to operationalize concepts of vulnerability and contribute to evidence-based policy making for risk reduction. The idea that groups of people have unequal vulnerability – that interacting factors such as poverty and access to political power differentially influence their capacity to anticipate, cope with, resist and recover from the impacts of hazards – is well established in the literature (Wisner, Blaikie, Cannon, & Davis, 2004). The concept extends to the differential vulnerability of places, whereby physical and socioeconomic attributes of communities exacerbate or ameliorate the potential impacts of natural hazard events (Cutter et al., 2008).

Indicator-based vulnerability analysis quantitatively represents and assesses important attributes of communities that contribute to their loss potential (Cutter, Boruff, & Shirley, 2003). Typical measures pertain to such aspects as population size, highly vulnerable socio-demographic groups, income, and building stock characteristics that represent what is at risk (exposure) and its susceptibility to loss (sensitivity). Similarly motivated studies of resilience analysis additionally incorporate indicators of communities' capacity to recover from disasters (e.g., Lam, Reams, Li, Li, & Mata, 2015). While the appropriate number and selection of indicators remains an area of debate (Stafford & Abramowitz, 2017), the suite commonly encompasses broad categories of the community's assets and capacities, referred to as capitals. These generally include social, economic, and built environment capitals; some frameworks variously include human, institutional, and/or natural capital (see Chang et al., 2015; Cutter, 2016).

Numerous studies have applied indicator-based approaches to assess the vulnerability of coastal locations and communities (Nguyen, Bonetti, Rogers, & Woodroffe, 2016). Some address coastal vulnerability generally (Frazier, Thompson, Dezzani, & Butsick, 2013) while others focus on vulnerability to specific hazards such as hurricanes and storm surge (Bjarnadottir, Li, & Stewart, 2011; Rygel, O'Sullivan, & Yarnal, 2006), tsunamis (Wood, Burton, & Cutter, 2010), marine oil spills (Santos, Carvalho, & Andrade, 2013), coastal erosion (McLaughlin & Cooper, 2010), loss of coastal wetlands due to urbanization (Huang, Li, Bai, and Cui, 2012), or coastal flooding and sea-level rise (Balica, Wright, & van der Meulen, 2012; Felsenstein & Lichter, 2014; Wu, Yarnal, & Fisher, 2002). Such applications draw attention to aspects of exposure particular to coastal hazard contexts, such as elevation and population in coastal zones. At the same time, they recognize the need to represent the many vulnerability attributes that are not coastally specific; for example, sensitivity attributes such as low income or elderly populations that are as relevant in extreme heat or earthquake events as in coastal floods.

The indicators-based approach to assessing vulnerability and resilience to hazards is popular largely because it produces findings that can be easily interpreted by policy makers, synthesizing complex information into a metric, or score, that can be relevant to policy decisions (Hinkel, 2011). Reducing the complexity of vulnerability to a quantitative measurement entails some limitations, however: indicators cannot fully capture the breadth, nuances, and interactions of factors that produce vulnerability (Adger, 2006; Barnett, Lambert, & Fry, 2008; Jones & Andrey, 2007; Rufat, 2013) or the dynamics of an evolving process (Cutter et al., 2008; Fekete, 2012; Mustafa, Ahmed, Saroch, & Bell, 2011). Recognizing that vulnerability is context-specific, some researchers have advocated incorporating input from people knowledgeable about local conditions in constructing indices that are locally relevant and meaningful to policy makers (Barnett et al., 2008; Frazier et al., 2013; Oulahen, Mortsch, Tang, & Harford, 2015).

While the preponderance of vulnerability indicator studies concerns relative vulnerability, recent studies have called for approaches with a different but related goal: discerning patterns, similarities, and differences in vulnerability (Chang et al., 2015; Cutter, Ash, & Emrich, 2016; Kok et al., 2016; Wood et al., 2015). Assessing relative vulnerability highlights places that may have "high" vulnerability, thereby supporting policy-makers in prioritizing localities for attention, allocating limited resources, and drawing attention to factors that cause people and places to be vulnerable. In contrast, similarity analysis identifies places that share vulnerability conditions. Results can support communities in seeking "peer" localities that may be confronting similar problems using similar strategies, regardless of whether or not they are considered to be highly vulnerable. The Hazard Vulnerability Similarity Index (HVSI) proposed by Chang et al. (2015) enables a one-to-many matching whereby an individual community can identify other similarly vulnerable places.

There remains a need to understand what types of coastal vulnerability exist and which are predominant. A typology of coastal communities can support higher levels of government in efficiently developing risk reduction guidelines that are more applicable to local contexts, and can facilitate establishing and augmenting networks of peer localities for knowledge exchange and advocacy. Cluster analysis, a family of statistical techniques for delineating groups of similar units, offers a well-established approach for developing a community typology. Researchers in applied geography have utilized cluster analysis to classify spatial units ranging from urban greenspaces (Kimpton, 2017) and urban neighborhoods (Delmelle, 2015) to fishing communities (Pollnac, Seara, Colburn, & Jepson, 2015) and vulnerable watersheds (Tran, O'Neill, & Smith, 2010). Applications are also emerging in the natural hazard and climate change fields, yielding typologies of highly vulnerable urban neighborhoods (Rufat, 2013; Stafford & Abramowitz, 2017), agricultural land vulnerability to climate change (Kok et al., 2016), and tsunami vulnerability (Wood et al., 2015). This paper applies cluster analysis methods to develop a typology of communities at risk of flooding and other coastal hazards.

3. Materials and methods

The methodological approach develops and demonstrates the value of a typology of coastal communities in three phases. A set of communities is first identified within the study region and characterized by a suite of hazard vulnerability indicators. Second, the communities are grouped according to their indicator profiles using cluster analysis, generating a typology of coastal communities in the region. The final phase addresses situations where new communities may wish to be matched to this established classification; for example, to access resources such as adaptation guidelines that have been tailored to different types of coastal communities. In this final phase, three new communities from outside the original set are matched to the typology from phase 2 using an index of similarity.

3.1. Study area

The methodological approach is demonstrated through a case study application in the Pacific coastal region of Canada. Specifically, the analysis includes the 50 largest coastal communities along the Strait of Georgia, the most populated region of the west coast (Fig. 1). These communities face similar coastal hazards related to climate change (e.g., storm surges, coastal erosion, and sea-level rise) and other marine risks such as tsunamis, shipping accidents, oil spills and contamination.

From a vulnerability perspective, the 50 communities exhibit considerable diversity in their geographic and socioeconomic attributes. Communities here consist of municipalities or areas deemed equivalent to municipalities for statistical reporting purposes (i.e., census

Fig. 1. Location of case study communities.

subdivisions in the Canadian Census). They range from small, rural, and remote communities dominated by natural resource or tourism industries, to large urban centres that are highly connected with more complex economies. The smallest has some 4000 residents, while the largest has over 600,000. The City of Vancouver and neighboring jurisdictions in the metropolitan region account for 17 of the communities. The 50 communities differ widely in terms of connectivity to urban and economic centres: some serve as hubs for road, marine, and air transport, while others are island communities wholly reliant on ferry services for transportation.

For the third phase of the analysis, three example communities were selected from the Atlantic province of Nova Scotia (Fig. 1). Separated by vast distances and different provincial governments, municipalities in British Columbia and Nova Scotia currently engage in minimal knowledge-sharing. While many British Columbia municipalities have initiated planning for climate change adaptation including sea-level rise (Baynham & Stevens, 2014), such efforts are challenged by funding deficiencies (BCREA, 2014). Nova Scotia, by contrast, mandated and financially incentivized municipalities to undertake climate change adaptation planning by 2014 (Vogel, 2015). The analysis considered three disparate Nova Scotia communities: Halifax, the provincial capital and largest city (pop. 390,000); Lunenburg, a tourism-oriented town (pop. 25,000); and Yarmouth, a fisheries town more typical of the region (pop. 10,000) that has undertaken climate change adaptation planning through a multi-sectoral collaborative partnership (Manuel et al., 2012).

3.2. Indicators data

For purposes of developing a coastal community typology, indicators were selected according to three broad principles, as described further below: breadth, relevance, and data requirements. Table 1 summarizes the 10 indicators selected. Note that indicator scales do not reflect judgments about the direction of influence of each vulnerability factor; that is, higher or lower values do not necessarily reflect higher or lower vulnerability, but rather, different modes of vulnerability.

The first selection principle, breadth, refers to the idea that the suite of indicators should span the range of important vulnerability factors identified in the literature. Breadth was considered by adapting the indicator framework proposed by Chang et al. (2015). This framework is structured according to different types of community assets or capitals: social, economic, built, and natural capital. As cluster analysis requires complete and comparable data, the analysis omitted a fifth capital, institutional, as is frequently done in vulnerability indicator studies (Oulahen et al., 2017). Following Chang et al. (2015), the indicator framework is further structured according to five dimensions that pertain to these capitals: size (resource availability, magnitude of exposure), spatial structure (geospatial aspects affecting vulnerability), composition (nonspatial aspects of community structure), integration (networks, access, and isolation), and change (temporal dynamics of vulnerability). For example, the indicator "number of businesses" concerns the size of the community's economic capital. As noted in Table 1, the selected indicators together reflect the array of community capitals and dimensions.

The indicator set also reflects breadth by capturing the exposure and sensitivity aspects of the broader concept of vulnerability. Exposure, referring to what is at risk of hazards such as flooding, relates to attributes such as community size (measured by number of businesses), coastal orientation of settlement (percent of population living on the coast), intensity of coastal development (predominant land use on the coast), property at risk (median housing value), and the extent of area at risk (coastline length). Sensitivity refers to the propensity to suffer loss if exposed to a hazard. Physical characteristics affect sensitivity; for example, landform steepness (measured here by coastal geomorphology) and building stock characteristics reflecting building codes and their improvements over time (percent of dwellings built before 1960). Spatial and socio-economic sensitivity attributes, which have been extensively studied in the literature, are captured parsimoniously here in terms of the community's economy (percent commuting outside the community for work, an indicator distinguishing suburbs from urban centres), vulnerable populations (percent not speaking one of the official languages, English and French), and resource-based economic activity tied to coastal and other natural resources (employment in the primary economic sector).

The second principle, relevance, was implemented with the research team's knowledge of the local context and through stakeholder engagement. For example, "population not speaking one of the official languages (English or French)" is an appropriate indicator of socially vulnerable groups and immigrant concentrations in the Canadian context. Stakeholder input was solicited through a workshop held in May 2015 that engaged 28 regional stakeholders from diverse localities and professions (e.g., municipal planners, engineers, emergency managers). Participants provided information on the most important indicators and capitals for their work, suggested specific indicators, and confirmed a shared view on the relevance of the selected indicators.

The third principle, data requirements, pertains to practical issues of implementation. For cluster analysis, indicator data should in this application be complete and comparable across communities. Data were therefore obtained primarily from publicly available federal and provincial government data sources, such as the Census of Canada (Table 1 above). Indicators were all normalized or log-normalized to a range of 0.0–1.0. Most of the indicators are continuous variables; those that

Table 1
Hazard vulnerability indicators.

Indicator	Vulnerability Concept	Capital	Dimension	Measure	Data Source
No. businesses with employees, 2013	Exposure	Econ.	Size	0 ~ 1[a]	BC Stats
Population living on coast, 2011[b]	Exposure	Social	Spatial structure	%	Census
Median housing value, 2011	Exposure	Built	Size	0 ~ 1[a]	NHS[c]
Coastal land use, 2012	Exposure	Built	Spatial structure	0–1 ordinal[d]	CanMap DMTI
Coastline length, 2011	Exposure	Natural	Size	0 ~ 1[a]	Census shapefiles
Population commuting outside municipality, 2006	Sensitivity	Econ.	Spatial structure	%	Census
Employment in primary sector, 2011	Sensitivity	Econ.	Composition	%	NHS
Population not speaking official language, 2011	Sensitivity	Social	Integration	%	Census
Dwellings built before 1960, 2011	Sensitivity	Built	Change	%	NHS
Coastal geomorphology, 2008	Sensitivity	Natural	Spatial structure	0–1 ordinal[e]	GeoBC

Notes:
[a] Logarithmic value of indicator normalized by range across the case communities.
[b] Percent of population residing in dissemination areas (DAs) on coast, determined using GIS analysis.
[c] National Household Survey.
[d] Classification of coastal land use based on level of vegetation, agriculture, and grey infrastructure within 500 m of shoreline; in five ordinal categories from "mostly green" to "mostly grey," with scale normalized 0–1.
[e] Classification of coastline steepness based on geomorphology and softness; in five ordinal categories from "mud, gravel and sand flats" to "rocky platforms, cliffs and man-made structures," with scale normalized 0–1.

were ordinal were treated as continuous in the cluster analysis (Everitt, Landau, Leese, & Stahl, 2011). To facilitate the empirical discovery of groups through cluster analysis, indicators should not be highly correlated (here, the Pearson's correlation coefficient for all pairs was less than 0.6).

3.3. Determining community types

Cluster analysis, a class of statistical techniques for discovering groups in data, was applied to develop an empirical typology of communities based on their indicator profiles. Many clustering methods are applicable and while selection guidelines are available, no single method can be unambiguously recommended (Everitt et al., 2011). The most common approach, hierarchical cluster analysis (HCA), was utilized here because of the relatively small sample size and implicit hierarchies in the subject matter, community types. Squared Euclidean distance was selected as the distance measure and complete linkage, which performs well when clusters are of different sizes, as the clustering method. The number of groups was determined from manual inspection of dendrogram results and comparison of intra- and inter-group variability. Each indicator was evaluated using analysis of variance (ANOVA) to determine its value for distinguishing the groups. Robustness of the resulting clusters was assessed through comparison with results from alternative cluster analysis methods, specifically *k*-means optimization and different distance measures, and reordering the data. To distinguish between communities that are similar in hazard exposure but different in sensitivity (and vice versa), communities were clustered independently according to the five exposure and five sensitivity indicators, respectively, then cross-tabulated. Such an approach, which resembles that of Wood et al. (2015), facilitates interpretation of results to characterize vulnerability types. As described in Section 4 below, the analysis yielded 10 coastal community groups. Each community type can be represented by the centrotype of the group, as defined by the mean value of each indicator.

3.4. Identifying corresponding types

The third phase of the analysis addresses situations where it may be beneficial to match a new community to an existing classification, for example, to join an existing collaboration or to access resources tailored for a type of community. Rather than run the cluster analysis with an amalgamation of prior and new communities, which risks altering and obscuring the prior classification, the analysis adopts an approach that enables matching new communities while preserving the original typology. As illustration, three new communities in Nova Scotia are matched to the 10 British Columbia (BC) community types. Data for the same set of 10 indicators (Table 1) were collected using the same data sources except for coastal geomorphology (based on Greenlaw et al., 2013) and number of businesses (based on Nova Scotia, 2010). The Nova Scotia communities are matched to the BC typology for both exposure and sensitivity using the Hazard Vulnerability Similarity Index (HVSI) (Chang et al., 2015). The HVSI measures the similarity between two communities based on their indicator profiles. HVSI can range from 0, indicating complete dissimilarity, to 1, indicating that the two communities are identical based on the selected indicators. For each Nova Scotia community, HVSI is calculated with the centrotype of each of the 10 BC community types, and the community is matched to the one with the highest HVSI score. In the HVSI calculations, all indicators are treated as continuous variables and the range for each indicator is the range for the 10 types and the three new communities.

4. Results

4.1. Determining community types

Cluster analysis results yielded three exposure groups and four sensitivity groups (see Appendix A for dendrograms). The resulting community types and their members are listed in Table 2 and mapped in Fig. 2, with each type labeled by its corresponding Exposure ($A \sim C$) and Sensitivity ($a \sim d$) clusters. As shown in Table 2, four of the types (*Aa*, *Ab*, *Ac*, and *Bc*) are predominant: These types individually account for 12–32% of the communities and together represent 80%. Six other types contain only 2–4% of the cases each, and two (*Ad* and *Cd*) do not include any. Analysis of variance (ANOVA) showed all the indicators to be statistically significant at the 10% level or better, confirming that each indicator contributes significantly to the resulting classification. Group membership was highly consistent with results from *k*-means clustering, with 82% correspondence for three exposure groups and 98% for four sensitivity groups. Randomly reordering the data did not affect grouping results.

The 10 community types are described in Table 3 on the basis of their salient characteristics. These qualitative descriptions derive from quantitative assessment of the indicator profiles for each type, taking into account the indicator means for each group in relation to the entire set of 50 communities (Fig. 3) and the intra- and inter-group variability for each indicator. In Fig. 3, similarities in exposure indicators (shaded green) can be seen across the types in each row, and in sensitivity indicators (shaded red) among the types in each vertical stack. Exposure

Table 2
Share of communities by type[a,b].

Exposure Group	Sensitivity Group				Total
	a	b	c	d	
A	**Aa*** 12%	**Ab*** 24%	**Ac*** 12%	-	48%
B	**Ba** 2%	**Bb** 4%	**Bc*** 32%	**Bd** 4%	42%
C	**Ca** 4%	**Cb** 4%	**Cc** 2%	-	10%
Total	18%	32%	46%	4%	100%

Notes:
[a] * = Predominant group, accounting for at least 10% of cases.
[b] Group membership, ordered by decreasing size within group: (Aa) Vancouver, Richmond, Victoria, Nanaimo, Squamish, Greater Vancouver A; (Ab) Langley, North Vancouver District, West Vancouver, Maple Ridge, North Vancouver City, New Westminster, Port Coquitlam, Port Moody, Oak Bay, North Saanich, Esquimalt, Ladysmith; (Ac) Surrey, Burnaby, Coquitlam, Saanich, Delta, Colwood; (Ba) Sechelt; (Bb) View Royal, Nanaimo A; (Bc) Langford, Courtenay, North Cowichan, White Rock, Central Saanich, Parksville, Pitt Meadows, Gibsons, Sidney, Comox, Qualicum Beach, Sooke, Comox Valley C, Comox Valley B, Cowichan Valley C, Nanaimo G; (Bd) Campbell River, Powell River; (Ca) Capital F, Capital G; (Cb) Nanaimo E, Metchosin; (Cc) Comox Valley A.

A communities are all urbanized places, but subgroups *Aa*, *Ab*, and *Ac* differ in key sensitivity attributes. Older, wealthier municipalities such as Vancouver (*Aa*) are distinguished from their suburbs (*Ab*) and newer growth areas (*Ac*). Exposure *B* communities are smaller and less wealthy, on the whole, while Exposure *C* communities are the smallest and most remote. Sensitivity *a* communities have the lowest out-commuting rates, while Sensitivity *b* places tend to be bedroom communities and *c* places, areas with more recent growth. For example, types *Ab*, *Bb*, and *Cb* represent three distinct forms of commuter communities. The two communities in type *Bd* are distinct as a group, exhibiting the least commuting share, the highest primary sector employment, and the flattest coastline.

While the coastal community typology is specific to the BC case, the methodology and findings contribute several general insights to the hazard vulnerability literature. First, an explicit criterion of breadth is important in developing indicator profiles as it fosters a balanced treatment of the range of factors that influence community vulnerability; for example, attention to both exposure and sensitivity aspects of vulnerability. Second, the typology discerns many different types of community-scale vulnerability. Contrasting levels of exposure and sensitivity in combination create different modes of vulnerability, which may not necessarily be higher or lower than others. This implies that some kinds of risk reduction and adaptation strategies may be more appropriate in some local contexts than in others. Third, examination of Fig. 2 reveals that communities with similar exposure tend to be spatially clustered, but those exhibiting similar sensitivity are more dispersed. Most municipalities in the highly urbanized regions around Vancouver and Victoria, for example, are classified in exposure group *A* (orange), while group *C* communities (purple) are all in island locations. Meanwhile, each sensitivity group (designated by circles and other shapes in Fig. 2) includes members on both sides of the Strait.

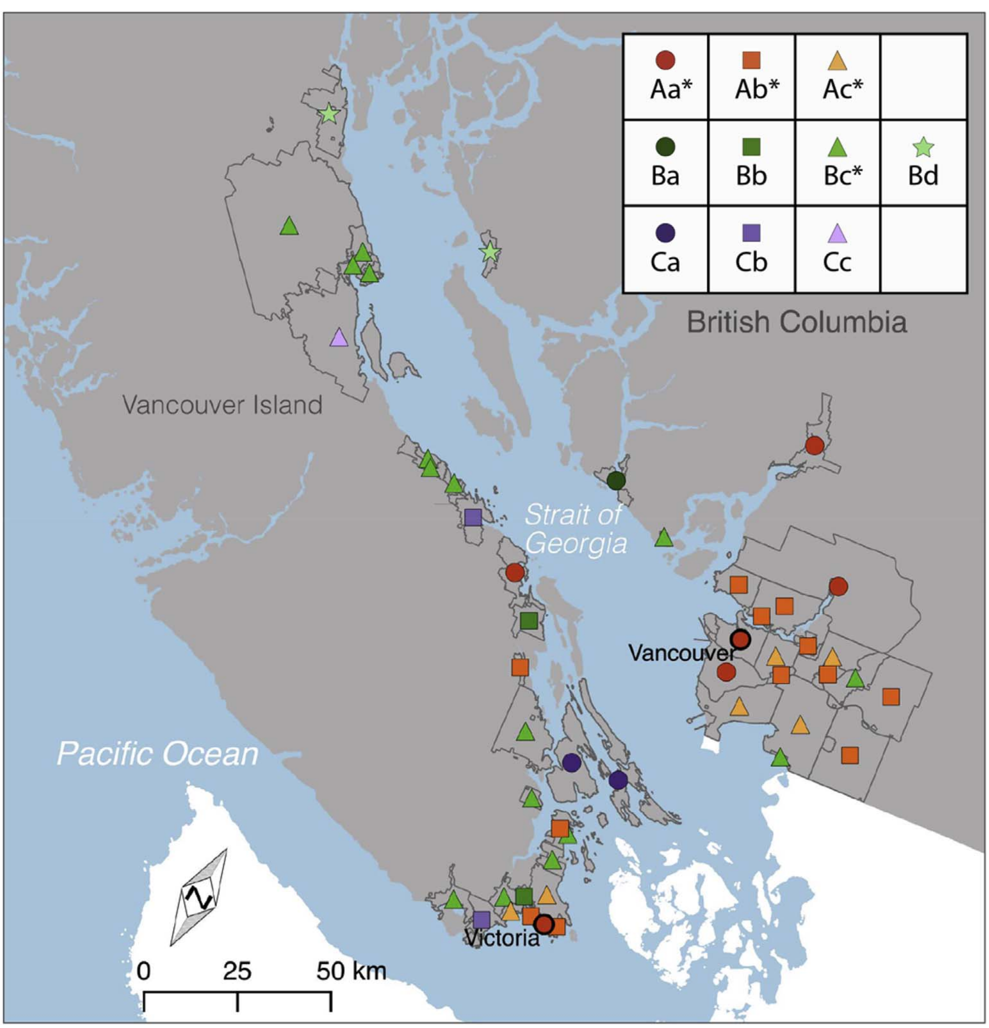

Fig. 2. Coastal communities classified by type.

Table 3
Coastal community typology.[a].

Type	Description
Aa*	Established city; developed coastline; higher property values; economy attracts immigrants
Ab*	Suburban community; semi-developed coastline; higher property values; commuting population
Ac*	Growing suburban city; semi-developed, flat coastline; higher property values; economy attracts immigrants
Ba	Growing small town; semi-developed, steep coastline with population concentrated on coast; lower property values
Bb	Small suburb; semi-developed coastline; commuting population
Bc*	Growing suburban town; semi-developed, flat coastline; lower property values
Bd	Older remote town; semi-developed, flat coastline; lower property values; resource-based economy
Ca	Small island community; mostly undeveloped coastline with population concentrated on coast
Cb	Small suburb; steep, mostly undeveloped coastline with population concentrated on coast; higher property values; commuting population
Cc	Small, established suburb; flat, long, undeveloped coastline with population concentrated on coast; lower property values; resource-based economy

Note:
[a] * = predominant types.

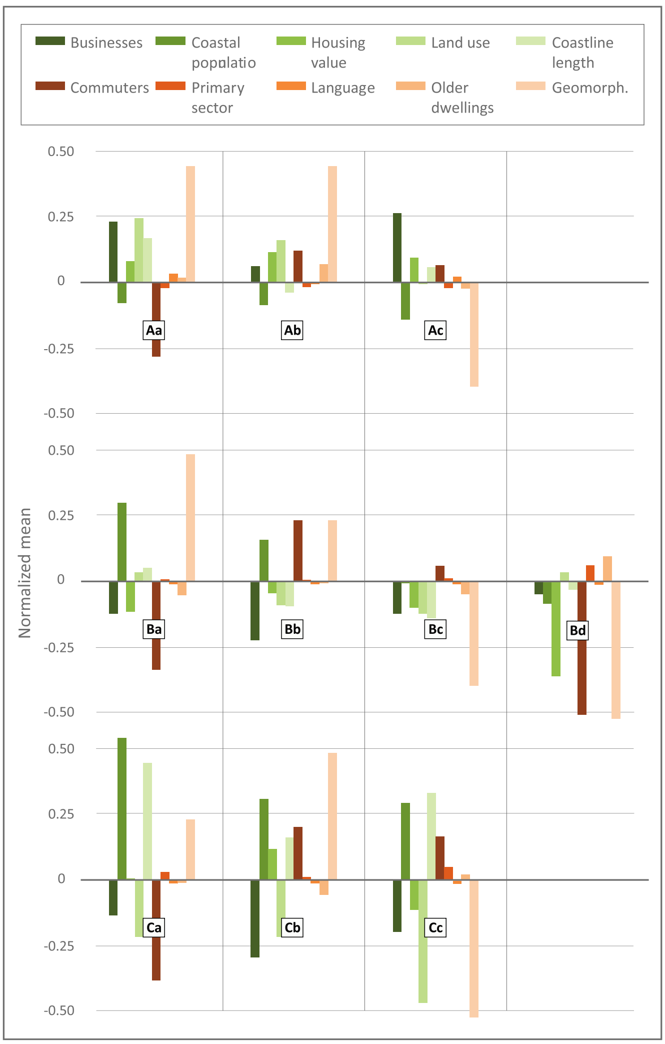

Fig. 3. Indicator Profiles for 10 Coastal Community Types. (Normalized mean values are the group means less overall mean, for each indicator.)

These findings highlight that exposure to a particular hazard, in this case coastal flooding, relates closely to physical geography whereas sensitivity is not so spatially contingent. Thus, since communities with similar sensitivity attributes may often be distant and disengaged from one another, risk reduction and adaptation networks may play an especially valuable role in sharing knowledge about sensitivity-related interventions.

4.2. Identifying corresponding types

Using the HVSI for both exposure and sensitivity indicators, Lunenburg, the tourism-oriented town in Nova Scotia, matches with community type *Ba* (HVSI = 0.826), characterized in Table 3 above as growing small towns with highly populated and semi-developed, steep coastlines and lower property values, and economies that are not primary sector oriented. This result is reasonable and consistent with the observation that the BC community in type *Ba,* Sechelt, is also a small, tourism-oriented town with a well-populated coastal area and rocky, steep coastline. Similarly, Yarmouth municipal district, a port and fishing settlement in Nova Scotia, is matched with type *Cc* (HVSI = 0.807), which represents small communities with significant dependence on the primary economic sector and a mostly undeveloped, flat coastline. Like Yarmouth, the BC jurisdiction of this type, Comox Valley A, encompasses vast forested areas, small islands, and many dispersed communities oriented toward fishing and tourism.

Considering the typical development characteristics of a major city, the HVSI result for Halifax Regional Municipality may be unexpected. Halifax was matched with type *Bd* (HVSI = 0.629), which is characterized by semi-developed coastal zone, as opposed to types *Aa* or *Ab* that represent highly urbanized and populated places. Closer inspection reveals, however, this result is reasonable since Halifax Regional Municipality, the census subdivision, extends well beyond the urbanized core of Halifax city. Halifax Regional Municipality was amalgamated in 1996 from the City of Halifax, City of Dartmouth, Town of Bedford, and Municipality of the County of Halifax. In comparison with the unamalgamated BC cities, it therefore encompasses a substantially larger land area with large tracts of wilderness and constituent settlements that range from the highly urbanized City of Halifax to agriculture-based communities in the County. The uniqueness of the Halifax Regional Municipality is also reflected by the moderately low HVSI score, which indicates that it does not match well with any of the 10 BC community types. The incongruity is important to recognize from a risk reduction standpoint, as it suggests that Halifax may be facing different risk reduction governance challenges and opportunities than British Columbia communities of comparable population size. The finding also highlights the need to include a wider range of communities in the development of community types.

5. Discussion

Within the literature on community vulnerability to hazards, an emerging line of research compares communities for purposes of identifying commonalities across places, thereby drawing attention to patterns of biophysical and social-economic attributes that influence how communities may be affected by hazards. This study empirically identified 10 coastal community types (of which four were predominant) for Pacific Canada that represent different modes of community vulnerability as characterized by various combinations of

exposure and sensitivity attributes. The methodological approach can be readily replicated for other regions and hazards. Additional analysis demonstrated how a similarity index (HVSI) can be applied to match new communities, for example from a distant region, to an existing classification. These results together provide an approach for facilitating knowledge sharing among communities that are similarly vulnerable.

Sharing knowledge, lessons, and resources among communities that are similarly vulnerable can facilitate risk reduction and climate adaptation decision-making that addresses local needs and contexts. With the emergence of networks such as the Rockefeller Foundation's 100 Resilient Cities initiative (www.100resilientcities.org), opportunities for cooperation and mutual learning across communities are proliferating. Community typologies support such efforts by identifying groups that may share similar challenges, needs, and contexts for risk reduction. This support may be especially valuable for connecting distant communities, as illustrated in the case of the Eastern and Western Canadian examples.

The coastal community typology developed in this paper is specific to the case study region, period of analysis, hazard, and indicator set selected. Further research should expand the inquiry empirically as well as conceptually. The BC typology should be verified with local planners and policy-makers. Examining coastal community types in other global regions and assessing changes in cluster membership over time represent fruitful areas for further study. Conceptually, the indicator basis should be augmented to consider aspects of community capacity that moderate vulnerability, such as institutional attributes of local government that affect risk management (Oulahen et al., 2017). Such efforts would all face the challenge – common to indicator-based analyses – of identifying consistent indicators and collecting comparable data across diverse places while ensuring that the data are appropriate and meaningful in the local context (Barnett et al., 2008). The method developed in this study, wherein the indicator set is selected in relation to criteria of breadth, relevance, and data requirements, is intended to provide a transparent yet flexible approach to help meet the need for more efficient, effective knowledge-sharing to address increasingly urgent problems of natural hazard risk.

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Appendix

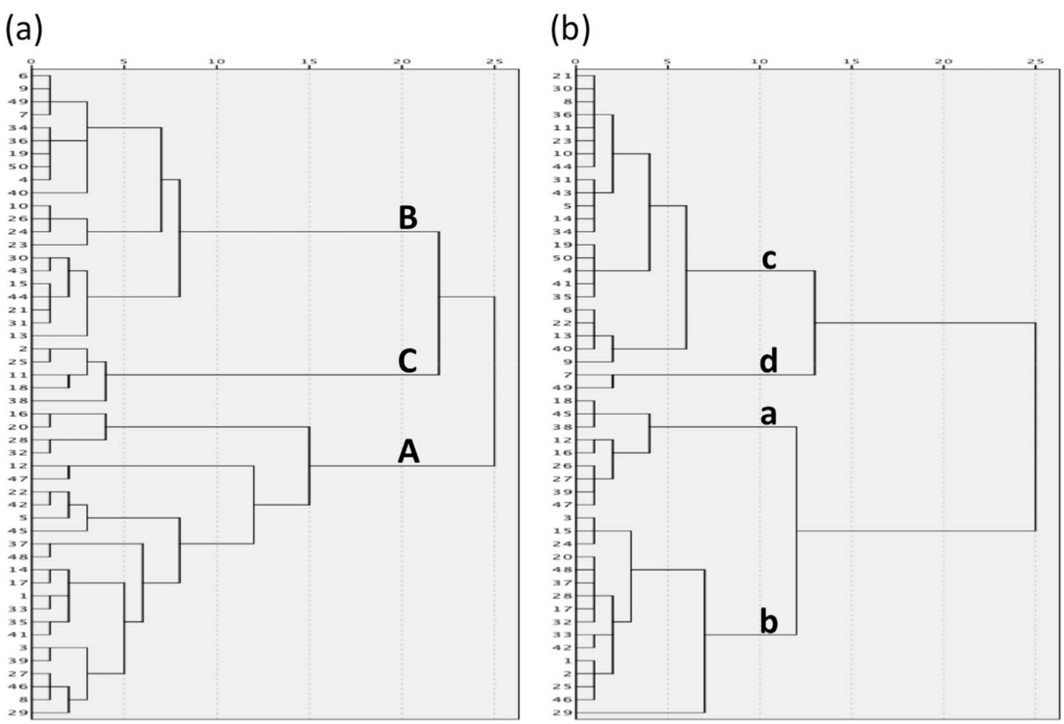

Fig. A1. Dendrograms for (a) exposure groups and (b) sensitivity groups. Groups are labeled in boldface.

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